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Is terrestrial water storage a useful indicator in assessing the impacts of climate variability on crop yield in semi-arid ecosystems?

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A R T I C L E I N F O

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A B S T R A C T

The productivity of global terrestrial ecosystems, especially in rain-fed agricultural systems and water-limited semi-arid ecosystems is largely restricted owing to climate-induced freshwater variability. In this study, Lake Chad basin (LCB) is selected as a tentative test bed to examine the utility of terrestrial water storage (TWS) inverted from Gravity Recovery and Climate Experiment (GRACE) measurements as a useful indicator in assessing the impacts of climate variability on annual crop yields (2003–2013) in a semi-arid ecosystem. Regression results show that changes in the temporal series of GRACE-derived TWS in LCB explained significant and higher proportion of variation (R^2 = 55%, 39%, and 32%, $p < 0.05$) in cashew nut, potatoes, and cowpea yields, respectively, compared to rainfall (R^2 = 2%, 1%, and 7%, respectively). Rainfall on the other hand, explained a higher (R^2 = 32%) variability in soybeans than TWS (R^2 = 2%). Model soil moisture indicated significant relationship ($p < 0.05$) with cowpea (R^2 = 48%), onions (R^2 = 44%), and cashew nuts (R^2 = 30%) somewhat similar to TWS. TWS nonetheless, showed relatively stronger and significant associations with four crops (i.e., cashew nut, potatoes, cowpea, and rice) than with soil moisture (except cowpea) and rainfall. By integrating TWS with rainfall as input variables to model crop yield data in a neural network system, the input variables are related to crop yield and showed some predictive potentials (r = 0.89 for cashew nut vs TWS/rainfall, $p < 0.05$), which can be improved considerably when longer times series of the data (especially TWS) are available for robust network training, testing, and validation. Large proportions of Africa and other non-industrialised regions of the world are heavily reliant on rainfed agriculture. Hence, multi-model climate forecasting studies in these regions can leverage on TWS not only as a soil moisture surrogate to assess the impacts of climate change on future scenarios of food production patterns, but as critical and resourceful input to food security analysis.

1. Introduction

Unfavourable hydro-climatic conditions in the Sahelian countries of West Africa, arguably have contributed to famine, decline of primary production, widespread desertification, and land degradation (see, e.g., Ndehedehe et al., 2016c; Knauer et al., 2014; Shiferaw et al., 2014; Tucker et al., 1991) and have resulted in several negative impacts on the socio-economic systems of the region. These impacts were the primary triggers of several ecosystem assessment based on Normalised Difference Vegetation Index (NDVI) and key hydrological indicators, e.g., rainfall and soil moisture (see, e.g., Andam-Akorful et al., 2017; Dardel et al., 2014; Jamali et al., 2014; Boschetti et al., 2013; Huber et al., 2011; Louise et al., 2014; Huber et al., 2011; Begue et al., 2011; Herrmann et al., 2005; Knauer et al., 2014). However, complex hydrological processes such as the well known 'Sahelian paradox', where despite the severe drought conditions of the 1970s and 1980s, an extensive network of well observations revealed that groundwater resources and water table in Niger increased tremendously due to changes in land use, amongst other factors (see, e.g., Descroix et al., 2009; Favreau et al., 2009; Séguis et al., 2004; Leblanc et al., 1997; Leduc et al., 2001). This phenomenon, which has also been reported in several other Sahel regions of West Africa (e.g., Gal et al., 2017; Mahé and Paturel, 2009; Mahé and Olivry, 1999) coupled with the restrictions of rainfall and soil moisture as hydrological indicators on surface vegetation dynamics in some parts of West Africa (e.g., Boschetti et al., 2013; Huber et al., 2011; Begue et al., 2011; Herrmann et al., 2005; Olsson et al., 2005), are notable challenges that warrants further understanding of the region's eco-hydrological processes and the impacts of climate variability.

In West Africa, a plethora of region and basin-specific studies have

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employed the latest satellite geodetic programme, Gravity Recovery and Climate Experiment (GRACE, Tapley et al., 2004) as a vital tool in hydrological research. These studies focused on a wide range of applications, e.g., in droughts (e.g., Ndehedehe et al., 2016c,b); terrestrial water budget closure (e.g., Ferreira and Asiah, 2015); hydrological characteristics, sub-surface water storage, aquifer system processes (see, e.g., Ndehedehe et al., 2016a, 2017a; Ferreira et al., 2014; Goncàlves et al., 2013; Nahmani et al., 2012; Henry et al., 2011; Hinderer et al., 2009); and evaluating the contributions of global climate teleconnections on regional dynamics of terrestrial water storage-TWS (an integrated sum of changes in catchment stores, e.g., groundwater and soil moisture; canopy; and surface waters) (e.g., Ndehedehe et al., 2017b). Given that the observed relationship between long term soil moisture changes and variations in some Sahelian vegetation was found to be inconsistent (Huber et al., 2011), more insightful studies using GRACE observations might be useful to further assess water-related impacts on the region's terrestrial ecosystem.

Over mainland Australia, GRACE-observed TWS explained variations in surface vegetation greenness at both inter-annual and seasonal time scales (Yang et al., 2014) while its role in modulating vegetation response to temperature changes in Eurasia has also been reported (A et al., 2015). This suggests its utility as a hydrological indicator of ecosystem performance in water limited ecosystems and Arctic biomes. However, the potential of GRACE-derived TWS in assessing the response of annual crop yields to the impacts of climate variability in data deficient, semi-arid regions (e.g., the Sahel) has not been reported. As mentioned in Chen et al. (2014), agricultural development and the productivity of the world's terrestrial ecosystems depends largely on water availability. In societies where the agricultural production systems are considerably reliant on rainfall, and for semi-arid regions that are presumably water-limited ecosystems, water deficit and extreme hydrologic variability remains a major restriction not only to vegetation growth but crop production and economic output (see, e.g., Yang et al., 2014; Hall et al., 2014; Piao et al., 2010). Hydrological variability has been identified as one of the key factors with adverse effects on the economic growth of non-industrialised regions (e.g., Hall et al., 2014; Brown and Lall, 2006), and represents a significant challenge to food security and infrastructure development. Lewis (2017) recently pointed out that one major aspects of underlying systemic causes of acute food insecurity in Ethiopia is the high proportion of small scale farmers who are heavily reliant on rainfed agriculture. Similar to Ethiopia and other sub-regions in Africa, the sensitivity of West Africa's agricultural production system and economy to climate variability is well known (see, e.g., Shiferaw et al., 2014; Cenacchi, 2014; Megersa et al., 2014; Ramarohetra et al., 2013; Roudier et al., 2011; Verdin et al., 2005; Vierich and Stoop, 1990). The strong variability of the West African Monsoon (WAM) on different time scales (e.g., inter-annual and multi-decadal), which brings about 70% of the annual rainfall (e.g., Sultan and Gaetani, 2016; Janicot, 1992) may impact adversely on agricultural systems, resulting in food insecurity and low national income. Because of this strong variability in the WAM system and large uncertainties and bias in regional climate projections (e.g., Todd et al., 2011; Roudier et al., 2011; Schuol and Abbaspour, 2006; Landerer and Swenson, 2000), quantifying the impacts of climate variations on agricultural yield is challenging.

While it is essential for government institutions to make informed and evidence-based decisions on appropriate indicators that will address specific policy issues relevant to food security governance (see, Pérez-Escamilla et al., 2017), understanding factors that impact on food availability is also critical. As mentioned in Brown and Lall (2006), one of the challenges to food production and national income is rainfall variability. According to Vörösmarty et al. (2005) who studied geospatial indicators of water stress in Africa, 25% of Africans are already experiencing water stress while an estimated 13% are direct recipients of drought-related stress once each generation. These indicators of water stress could have significant impact on a considerable proportion of Africa's agricultural biomes, which are mostly found in arid regions. For those regions where agricultural systems are devoid of sophistication yet account for a significant proportion of the gross domestic product (GDP), water stress and increased rainfall variability could translate to food insecurity, social conflicts, and poverty.

Cenacchi (2014), for example, noted that drought is a major constraint for crop and livestock production in Africa and across Asia. In a compendium of 16 related studies over West Africa (see, Roudier et al., 2011 and the references therein), there is evidence that climate change impact negatively on crop yield. Further, quasi-periodic phenomenon such as the El-Niño Southern Oscillation (ENSO) episodes have shown statistically significant association with some crops in the Sahel region (e.g., Okonkwo and Demoz, 2014). It is even anticipated that the impacts of global warming in the future will impact negatively on subsistence farming in several African countries (Verdin et al., 2005). As most climate projections suggest, the result of drought intensity in some areas around the world may lead to risk of crop losses (Cenacchi, 2014). In West Africa where an estimated 70% of the world's cocoa is produced, Schroth (2016) noted that drought years caused by El-Niño episodes affected cocoa yields. In addition to this, it has been shown that ENSO play significant roles in the characteristics of extreme climatic conditions in West Africa (e.g., Ndehedehe et al., 2016b; Paeth et al., 2012; Nicholson et al., 2000), and largely contribute to the temporal and spatial distributions of TWS in the region (e.g., Ndehedehe et al., 2017b). The impacts of climate change on agro-ecosystems are mostly channelled through hydrological drivers such as precipitation, soil moisture, and available freshwater. Consequently, there is a further need to diagnose the suitability of GRACE-derived TWS in assessing the impacts of climate variations on crop yield, particularly when rainfall and soil moisture have shown some weakness in the semi-arid Sahel as indicators of water availability (e.g., Dardel et al., 2014; Huber et al., 2011; Olsson et al., 2005).

In this study, the potential of GRACE-derived TWS as a useful terrestrial moisture surrogate in mapping the impact of hydrological conditions on annual crop yield in the Lake Chad basin (semi-arid Sahelian region-Fig. 1) is examined. The assessment of GRACE-derived TWS with crop yield data has become necessary given the (i) restrictions of rainfall as a hydrological indicator on terrestrial ecosystems and regional land surface phenology (e.g., Knauer et al., 2014; Seghieri et al., 2012; Chen et al., 2014; Yang et al., 2014), (ii) uncertainties in water budget estimates (e.g., A et al., 2015; Zhang et al., 2009), (iii) the morphological and physiological adaptations of Sahelian vegetation, which results in complex water use mechanisms during the dry season (e.g., Guan et al., 2014; Seghieri et al., 2012; Huber et al., 2011), and (iv) lack of considerable investments in observational networks for ecological and hydrological applications.

2. Assessing the impacts of climate variability on food security in the Lake Chad basin

2.1. The region

The Lake Chad Basin (LCB) is the world's largest interior drainage basin covering an approximate area of 2,500,000 km^2, and supports an estimated 37 million people who depend on its water resources for economic and domestic purposes (e.g., Ndehedehe et al., 2016b and references therein). Geographically, the basin is seated in the transition zone between the Sahara Desert and the tropical Sudano Sahel region of West Africa. Specifically, it is located between latitudes 6°N and 24°N and longitudes 7°W and 24°E and is occupied by Lake Chad at the centre (Fig. 1). The impact of persistent and long drought episodes of the 1960s and 1980s in the basin resulted in a significant contraction of the Lake Chad surface area (see, e.g., Ndehedehe et al., 2016b; Wald, 1990; Birkett, 2000; Coe and Foley, 2001; Lebel et al., 2003; Lemoalle et al., 2012). Rainfall is annual, occurring mostly between July and September. The basin is one of the Sahel regions that is highly vulnerable to

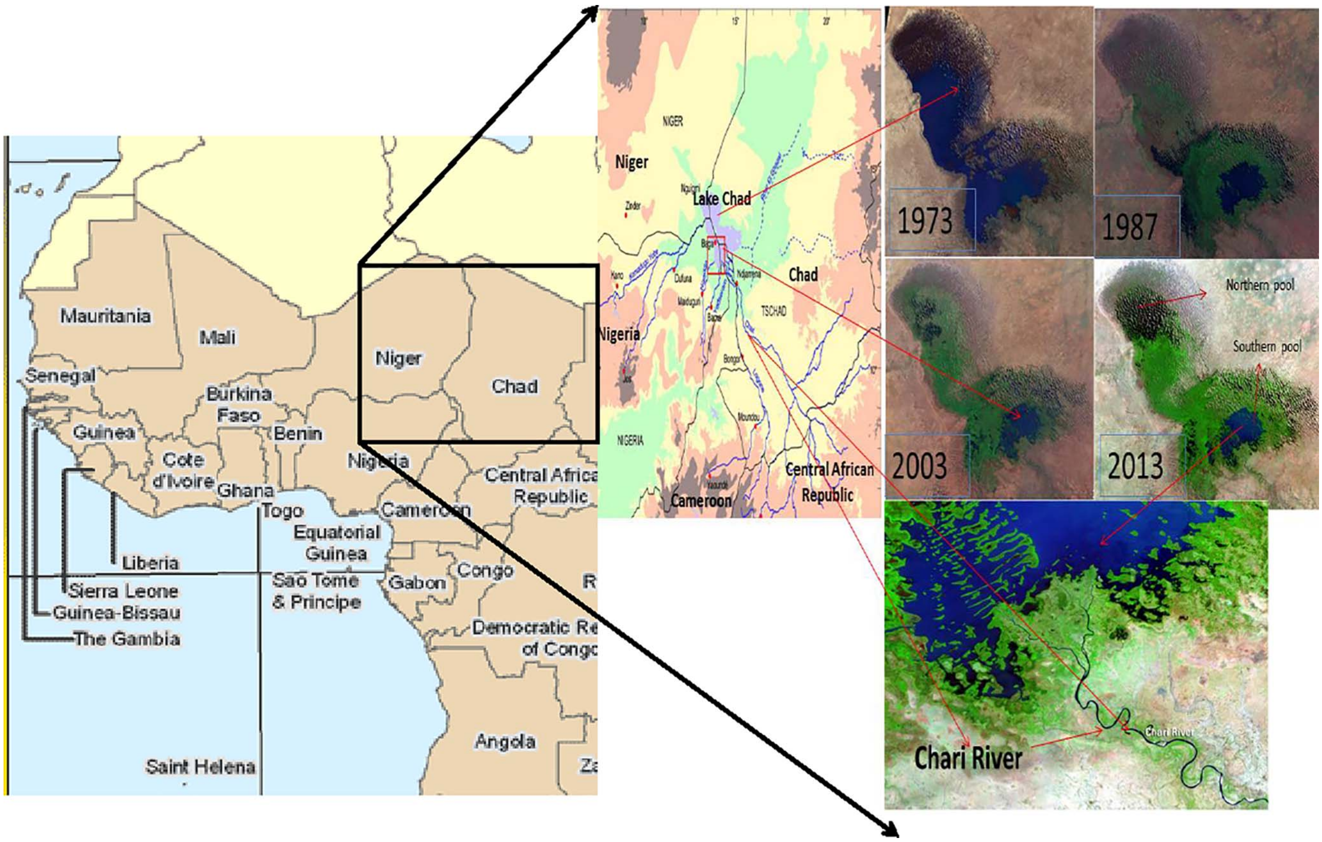

Fig. 1. Study area showing the riparian countries that constitute the Lake Chad basin and important river networks (blue line) within the basin. The contraction of the Lake Chad surface area owing to the impacts of climate variability for 1973, 1987, 2003, and 2013 are indicated. Map is adapted and modified from Figs. 1 and 2 of Ndehedehe et al. (2016b). (For interpretation of the references to colour in this figure caption, the reader is referred to the web version of this article.)

the impacts of climate variability and in most cases resulting in extreme drought and water deficit conditions. The various morphological transformations of the lake owing to several drought episodes in the region are indicated in Fig. 1. Whereas the northern catchment is predominantly arid, the southern catchment is hydrologically active because of the Chari/Logone River system, Komadougou-Yobe, and other minor rivers (Fig. 1). These rivers transport more than 95% of the river flows that nourish the Lake Chad (e.g., Ndehedehe et al., 2016b; Coe and Birkett, 2004). Although the desiccation of the Lake Chad was largely attributed to extreme droughts in the region, water withdrawals from the Lake for irrigation purposes during water deficit periods (see, e.g., Birkett, 2000; Coe and Foley, 2001) compounded the effects of these drought episodes. Apparently, this underscores the role of human activities in not only exacerbating the impacts of climate variability but in also reshaping the stability of Lake's ecosystem.

2.2. Climate change and food security

Ecosystems and global biodiversity are generally predisposed to adapting to the prevailing climatic conditions. As noted in a recent Food and Agricultural Organization report (FAO, 2016), when these conditions change, plants and animals will be impacted adversely, mostly in a profound way that diminish productivity and poses additional risk to agricultural production. The impacts of climate change on agro-ecosystems, be it direct or remote, could be enormous-impacting on crop yields and quality, market prices, ecosystem services, national income, and agricultural and other forms of livelihood. Both at region and global scales, not only is climate change expected to increase variability in crop yields in several regions of the world, there is evidence that it has adversely affected crop yields (e.g., FAO, 2016 and the references therein). This, without doubt will have enormous impacts on food security and livelihood. As large segments of the West African Sahel are heavily reliant on rainfed agricultural systems, the impacts of climate variability on freshwater and ecosystem dynamics would be more devastating. The human-modified droughts of the Lake Chad basin, for example, is typical of the Anthropocene, where various forms of human activities and climate change impact on catchment storage, soil properties, and hydrological processes, thereby modifying or amplifying the severity of such droughts. The combined effects of human activities, climate variability and land surface conditions in the basin could restrict prominent hydrological controls (rainfall and soil moisture) as indicators of ecosystem performance. Apart from increasing water stress under a climate change scenario, significant constraints to estimating the impact of climate change on future freshwater availability have been identified and includes, bias and model uncertainties in rainfall prediction output of climate models even at finer spatial scales; and the fact that changes in rainfall do not show a linear response to water availability (e.g., FAO, 2016; Todd et al., 2011; Schuol and Abbaspour, 2006; Landerer and Swenson, 2000). Other reports (e.g., A et al., 2015; Zhang et al., 2009) argued that uncertainties in regional precipitation estimates and water budget indicators are major challenges in understanding vegetation response to water constraints. Because of these issues, GRACE-derived TWS (Section 4.2) is introduced as a new hydrological state variable to help assess the impact of climate variability on annual crop yield in a semi-arid ecosystem. One important message in this assessment would be that it will enhance our understanding of the effects and role of climate on food security and nutrition in the region.

3. Data and methods

3.1. Data

Terrestrial water storage (TWS) product used in this study was derived from the GRACE (Tapley et al., 2004) satellite mission. The mission provides an integrated sum of changes in surface waters, catchment stores (e.g., groundwater, soil moisture, etc.), and canopy based on the observations of the Earth's time variable gravity fields. GRACE observations have been extensively used to study the Earth's water storage changes at regional, continental, and global scales (e.g, Ndehedehe et al., 2016b; Swenson and Wahr, 2007; Wouters et al., 2014 and the references therein). In this study, the GRACE Release-05 (RL05) spherical harmonic coefficients obtained from Center for Space Research (CSR, http://icgem.gfz-potsdam.de/ICGEM/shms/monthly/csr-rl05/) covering the period of 2002–2014, are used to estimate TWS over the region on a $1° \times 1°$ grid following the approach of Wahr et al. (1998) as

$$\triangle TWS(\phi,\lambda,t) = \frac{R\rho_{ave}}{3\varrho_w}\sum_{l=0}^{l_{max}}\frac{2l+1}{1+k_l}\sum_{m=-l}^{l}P_{lm}(\phi,\lambda)\triangle Y_{lm}(t), \quad (1)$$

where $\triangle TWS$ is the equivalent water height (hereafter TWS) for each month in time (t), and ϕ and λ are the geodetic latitudes and longitudes, respectively. R is the mean radius of the Earth (i.e., 6378.137 km), ρ_{ave} is the average density of the Earth (5515 kg/m^3), ϱ_w is the average density of water (1000 kg/m^3), k_l is the load Love numbers of degree l,P_{lm} are the normalized spherical harmonic functions of degree l and order m with $l_{\max} = 60$ and $\triangle Y_{lm}$ are the normalized complex spherical harmonic coefficients after subtracting the long term mean. Due to signal attenuation, which causes noise in the higher degree coefficients (e.g., Swenson and Wahr, 2002), the regularization filter of Kusche et al. (2009) was applied on the spherical harmonic coefficients in order to reduce the effect of the correlated noise. As this process of regularizing GRACE-observations usually result in leakage, the damping of the signal amplitude was compensated for using the Landerer and Swenson (2012) approach. This approach, which has been widely employed in a plethora of GRACE-hydrological studies (see, e.g., Wiese et al., 2016; Sun et al., 2016; Long et al., 2015; Fenoglio-Marc et al., 2012) derives a gain factor k by minimizing the misfit between the unfiltered and filtered storage time series based on simple least square regression (see, Landerer and Swenson, 2012). This gain factor is applied to the gridded fields of GRACE data to recover the geophysical signals that were lost as (e.g., Ndehedehe et al., 2016a; Sun et al., 2016)

$$TWS'(\phi,\lambda,t) = TWS*k(\phi,\lambda), \quad (2)$$

where TWS' is the GRACE-derived TWS corrected for leakage. This reduces the variance of the leakage error by more than 80% (e.g., Landerer and Swenson, 2012). Further, averaged TWS (i.e., W) values over the basin were computed using the area weighted average (see, e.g., Ndehedehe et al., 2016c):

$$\triangle W(\chi;t) = \sum_{l=1}^{n}\triangle W(\phi_i,\lambda_i,t)\frac{A_i}{A_\chi}, \quad (3)$$

where χ is the basin index, n is the number of pixels in the basin, A_i is the area of the grid cell i in χ and A_χ is the total area of χ. As opposed to GRACE applications in studies of droughts and floods (see, e.g., Ndehedehe et al., 2016b; Thomas et al., 2014; Reager et al., 2014; Yirdaw et al., 2008), it is employed here as a tool for assessing the impacts of climate variability on crop yield. In the remainder of the manuscript GRACE-derived TWS is simply referred to as TWS. Since TWS are monthly anomalies, they were aggregated to yearly values in order to be consistent with annual crop data.

Further, selected national annual crop yield data for Nigeria (soybeans, cashew nut, cowpea, and potatoes) and Chad (beans, onions, potatoes, and rice) during the 2003–2013 period were downloaded from the Food and Agricultural Organisation's (FAO) website (http://faostat3.fao.org/download/Q/QC/E). Also, precipitation from Tropical Rainfall Measuring Mission (TRMM) 3B43 (Kummerow et al., 2000), covering the period 2002–2013 is used in this study to examine the response of annual crop yield to rainfall variability. The data has a global coverage (50°S and 50°N) with a spatial resolution of $0.25° \times 0.25°$ and is available at the National Aerospace and Space Administration (NASA) Goddard Space Flight Center (GSFC) website (http://disc.gsfc.nasa.gov/datacollection/TRMM3B43-V7.shtml). Further, monthly CPC model soil moisture data (Fan and Dool, 2004) with spatial resolution of $0.5° \times 0.5°$ was used to investigate the response of crop yield data to soil moisture. Ideally, soil moisture is the most suitable indicator for studying the response of plants to climatic changes (e.g., Chen et al., 2014). However, it has shown weak relationship with surface vegetation greenness in the Sahel region (e.g., Huber et al., 2011). It would therefore be logical to compare its relationship with crop yield data to observed outcome of TWS-crop yield relationship. The CPC model soil moisture data is freely available at National Oceanic & Atmospheric Administration (NOAA) (http://www.esrl.noaa.gov/psd/data/gridded/data.cpcsoil.html) for download. In the remainder of the manuscript, the CPC model soil moisture is simply referred to as soil moisture for convenience. MODIS derived monthly evapotranspiration estimates with a spatial resolution of $0.5° \times 0.5°$, covering the period 2000–2014 are also used in the study to determine available freshwater over LCB expressed through net precipitation (e.g., Andam-Akorful et al., 2017). The ET data is available for download at the Earth Observing System of NASA's website (http://www.ntsg.umt.edu/project/mod16).

3.2. Method

The association of TWS anomalies and TRMM-based precipitation to these crop yield data is evaluated using a simple linear regression model (note that only normalised units of the data are used). Regression analysis is a popular statistical technique for investigating and modelling the relationship between variables. To establish the relationship between n paired data series (x_i,y_i), the expression is given as

$$y' = \beta_0 + \beta_1 \cdot x + \varepsilon, \quad (4)$$

where y' is the target data (response or dependent variable) and x is the independent variable (predictor), β_0 and β_1 are constants and ε is the error term, which can be minimized in the least square sense by defining an error function, ξ as

$$\xi = \frac{1}{n}\sum_{i=1}^{n}\varepsilon_i^2 = \frac{1}{n}\sum_{i=1}^{n}(y'-y_i)^2, \quad (5)$$

such that the error function becomes the sum of the squared differences between the data series and the linear equation. Coefficient of determination (R^2) is employed to measure the proportion of variance in the dependent variable (y') that is explained by the independent variables (x) in the linear regression model. The null hypothesis of no relationship between two variables is tested using the Student-t distribution test ($\rho < 0.05$). Further, TWS was integrated with rainfall in an Artificial Neural Network (ANN) framework to model their relationship with crop yield. ANN models are widely used machine learning applications for forecasting purposes. Our motivation for the ANN model is because they are flexible computing frameworks and universal approximators that can be used in several forecasting problems with relatively high accuracy (e.g., Khashei and Bijari, 2010). The relationship between the output (y_t) and the inputs (y_{t-1},...,y_{t-p}) can be represented mathematically as (e.g., Khashei and Bijari, 2010)

$$y_t = w_0 + \sum_{j=1}^{q} w_j.\, g\left(w_{0,j} + \sum_{i=1}^{p} w_{i,j}.\, y_{t-i}\right) + \epsilon_t, \quad (6)$$

where w_j ($j = 0,1,2,3,...,q$) and $w_{i,j}$ ($i = 0,1,2,3...,p$,$j = 1,2,3,...,q$) are the

model parameters referred to as the connection weights; p and q are number of input nodes and hidden nodes, respectively. The network performs a nonlinear functional mapping from the observations (rainfall and TWS) to the predicted value (crop data) similar to a nonlinear auto-regressive model. The model's performance is assessed by dividing the input data into training and test samples. There is no systematic rule in choosing q as it is largely data-dependent. Other implementation protocols include choosing the number of hidden nodes appropriately and the selection of the number of lagged observations, p, and the dimension of the input vector (e.g., Khashei and Bijari, 2010). The predictive performance of the model is improved based on the data presented to the network (e.g., Herrera et al., 2010). Details about the types of activation functions and implementation guidelines for developing ANN model can be found in Maier and Dandy (2000).

4. Results

4.1. Hydrological drivers in the Lake Chad basin

Understanding hydrologic drivers of the LCB is crucial to assessing the influence of variations in regional climates on agricultural systems. As shown in Fig. 2a, rainfall is poorly associated with TWS (r = 0.37) but shows maximum correlation (r = 0.89) at approximately two months lag. Although rainfall leads TWS by two months in much of West Africa (Ndehedehe et al., 2016a), observed phase shift between rainfall and TWS could go up to 90 days in other regions (e.g., Sun et al., 2016). TWS is strongly associated with soil moisture (r = 0.95) with the former indicating a rather similar peak-to-peak amplitude during the period as soil moisture (Fig. 2b). The CPC model soil moisture, which is derived from gauge rainfall and reanalysis-derived temperature data could be a very useful complementary data in hydrological studies of the region. Essentially, the strong TWS-soil moisture relationship represents variations of soil moisture components in the GRACE water column. Similar to Fig. 2a, monthly net-precipitation in Fig. 2c shows a considerable lower association with TWS (r = 0.26) but indicates a maximum correlation (r = 0.85) at two months lag. Net-precipitation can be used as a hydrological indicator to depict the state of available freshwater flux (e.g., Andam-Akorful et al., 2017). It can be combined with TWS to evaluate water budget more comprehensively. For example, years when TWS indicated higher pronounced peaks than net-precipitation (e.g., 2006–2012, Fig. 2c) were characterised by excess water evident in strong positive values of standardised precipitation index and increased Lake Chad water levels (e.g., Ndehedehe et al., 2016b). On the other hand, years when TWS and net-precipitation have similar peak amplitudes (e.g., 2002–2004, Fig. 2c) are either marked by excessive ET or characterised by drought conditions. The years between 2002 and 2004 actually coincided with extreme low water levels of Lake Chad and location-specific water deficit condition in the LCB (Ndehedehe et al., 2016b). As noted in FAO (2016), increased demand for water during ET process by vegetation and crops, caused by a rise in temperature will result in rapid soil moisture loss. If increasing temperature is considered an indication of high evaporative demand (the rate of water loss from a wet surface), in dry tropics where atmospheric conditions regulate the development, population and the life span of canopy phenology (Do et al., 2005), TWS would better account for plant water availability. Hence, as soil moisture is strongly associated with TWS (Fig. 2b), the latter apparently would be the most critical hydrological unit for assessing the impacts of climate variability on annual crop yield in the riparian countries of the LCB, given its water column and depth. Soil moisture may also be useful in such assessment but the lack of moisture observational networks coupled with the uncertainties and restrictions in satellite and model estimates of soil moisture (e.g., Yang et al., 2014; Dirmeyer et al., 2004; Njoku and Entekhabi, 1996) however, are challenging issues for the region. TWS therefore becomes an ideal and available hydrological unit to support the knowledge of climatic influence on the region's agricultural systems, especially given the structural formation of vegetation in the semi-arid Sahel region, which may be subject to complex water

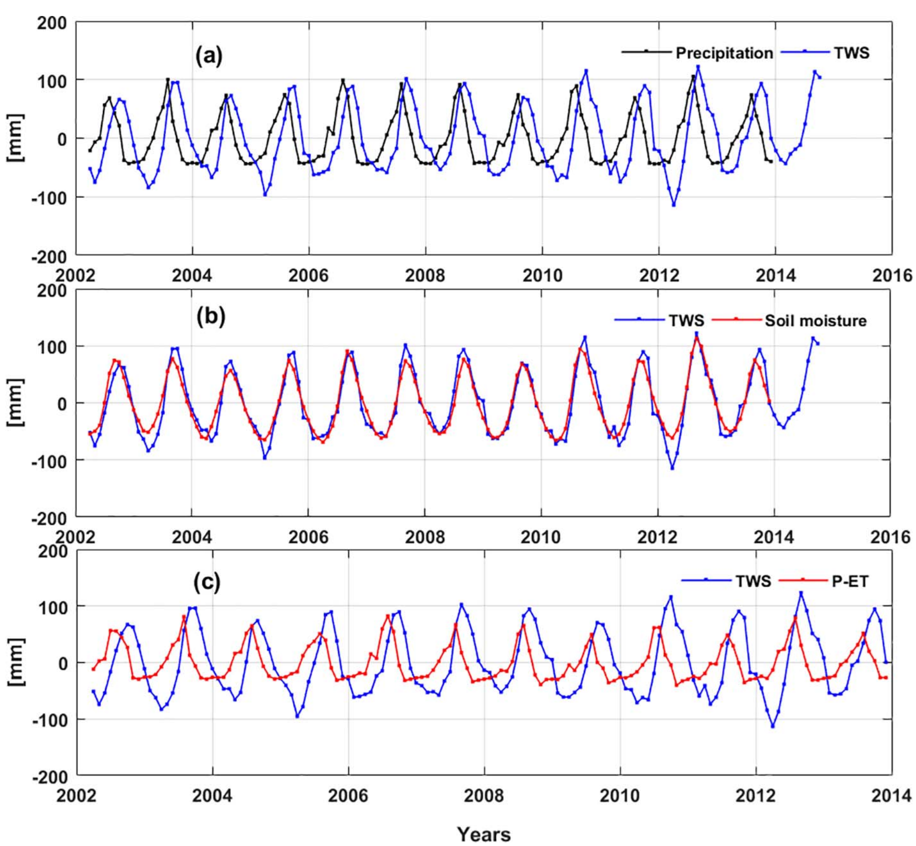

Fig. 2. Hydrological drivers of the Lake Chad basin. The observed relationships of monthly anomalies after removing the mean for the common period (2002/04–2013/12) is indicated for (a) precipitation vs TWS, (b) TWS vs CPC model soil moisture, and (c) TWS vs available freshwater flux expressed as net-precipitation (difference between precipitation and evapotranspiration over the basin). Cross correlation was used to examine the time lag (months) in which maximum correlation is observed for the rainfall-TWS and TWS-net-precipitation relationships in (a) and (c), respectively.

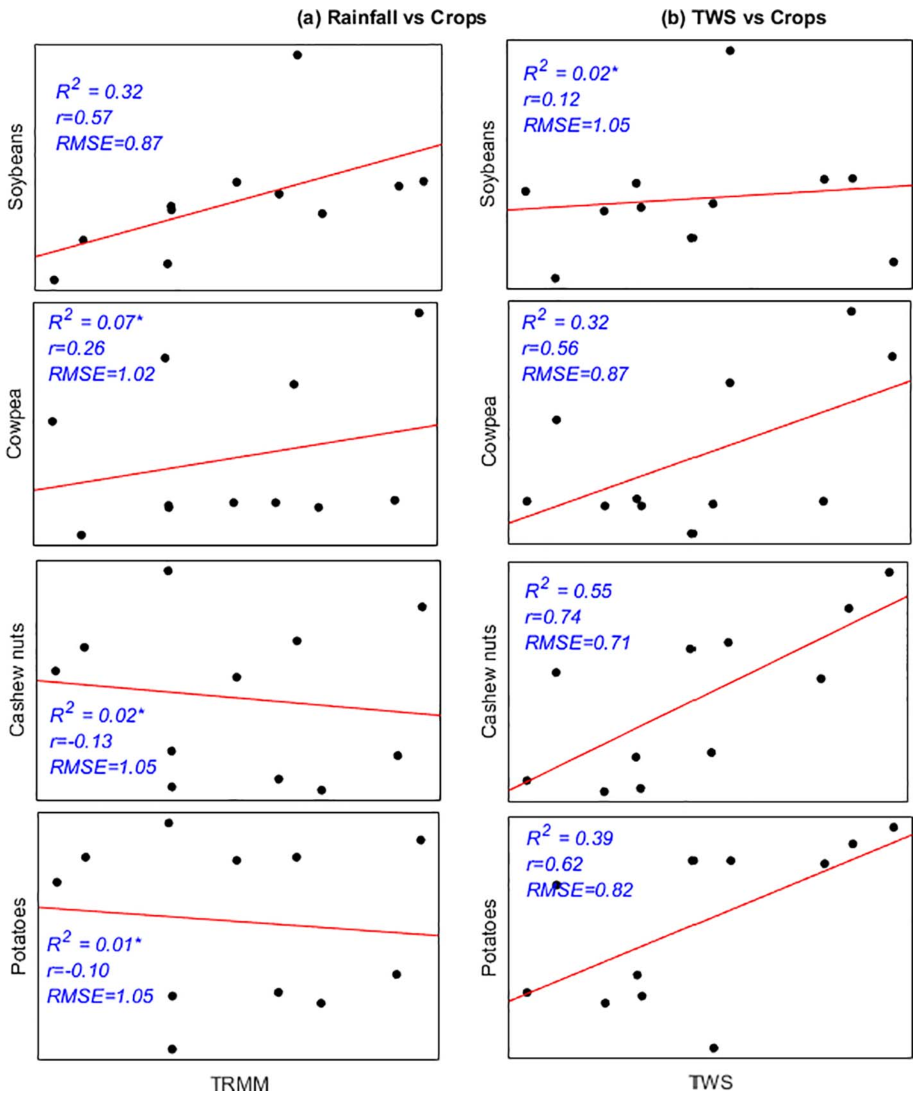

Fig. 3. Comparing the response of TWS and rainfall to crops in northern Nigeria. (a) Relationship between annual crop yield in Nigeria and average annual TRMM based precipitation anomalies over Lake Chad basin and (b) relationship between annual crop yield in Nigeria and TWS anomalies in the Lake Chad basin. The crop yield data and TWS are in normalised units. Other regression outputs such as the slope values (r) and root mean square errors (RMSE) are also indicated. Asterisks ($*$) show that the observed relationship is not statistically significant ($\rho < 0.05$).

use during the dry season (e.g., Guan et al., 2014; Seghieri et al., 2012; Huber et al., 2011).

4.2. The influence of TWS on annual crop yields

Two riparian countries of the LCB (i.e., north-east Nigeria and southern Chad) have been used here as tentative test beds to examine the potential of GRACE-derived TWS as a soil moisture surrogate to monitor the influence of climate on crop yield. The regression of annual crops in Nigeria with TWS and rainfall indicate that soybeans are more influenced by rainfall anomalies ($R^2=32\%$) while cowpeas, cashew nuts, and potatoes are more associated with TWS anomalies (R^2 = 32%, 55%, and 39%, respectively). Their R^2 and linear correlation (r) values suggest that rainfall and TWS explain fairly significant proportion of the variability in the aforementioned crops (Fig. 3a-b). In Chad, contrary to rainfall, which shows no significant association with any of the crops ($p > 0.05$), TWS anomalies explain more variabilities in potatoes and rice. Specifically, TWS anomalies explain a higher variability in potatoes and rice (34% and 32%, respectively) in Chad compared to rainfall, which indicates a rather little association with the same crops (Fig. 4). Unlike in Nigeria where rainfall was found to explain slightly higher proportion in the variability of soybeans than TWS anomalies (Fig. 3a), in Chad, beans has no relationship with either rainfall or TWS (Fig. 4a-b). Overall, rainfall shows a significant association with only soybeans (Fig. 3a) while TWS is associated with cashew nut, cowpea, potatoes, and rice (Figs. 3b and 4b).

The regression results of soil moisture with cashew nuts (R^2 = 30%) and cowpea (R^2 = 48%) in Nigeria (Fig. 5a) are somewhat similar to those of TWS in Fig. 3b as they are generally statistically significant ($p < 0.05$). Whereas TWS comparatively indicates a better association with cashew nuts (R^2 = 55%; r = 0.74) compared to soil moisture, on the other hand, soil moisture is more associated with cowpea (R^2 = 48%; r = 0.69) compared to TWS (R^2 = 32%; r = 0.56). Again, TWS actually indicated significant relationships with more crops (Figs. 3b and 4b) unlike soil moisture (Fig. 5a and b). Be it Nigeria or Chad, potatoes showed significant relationship with TWS (R^2 = 39% and r = 0.62;R^2 = 34% and r = 0.59, respectively, Figs. 3b and 4b) unlike soil moisture, which indicated no significant relationship with potatoes despite a near-moderate correlation value of 0.46 (Fig. 5a). In Chad, the relationship of TWS to potatoes and rice are significant (R^2 = 34% and r = 0.59;R^2 = 32% and r = 0.57; respectively, $p < 0.05$) unlike soil moisture that indicates no significant association with these crops (Fig. 5b), though a significant relationship exist between soil moisture and onions (R^2 = 44%). Fig. 6 shows the neural network results of combining TWS and rainfall as input variables to model the crop yield data. The model output, which also shows the nature of the best-fitted network (validation performance) in terms of their mean squared error indicates cashew nut can be predicted better with some degree of accuracy by integrating TWS with rainfall (r = 0.89, Fig. 6a) as opposed to other crops (Fig. 6b-d). Although the forecast experiment is limited by

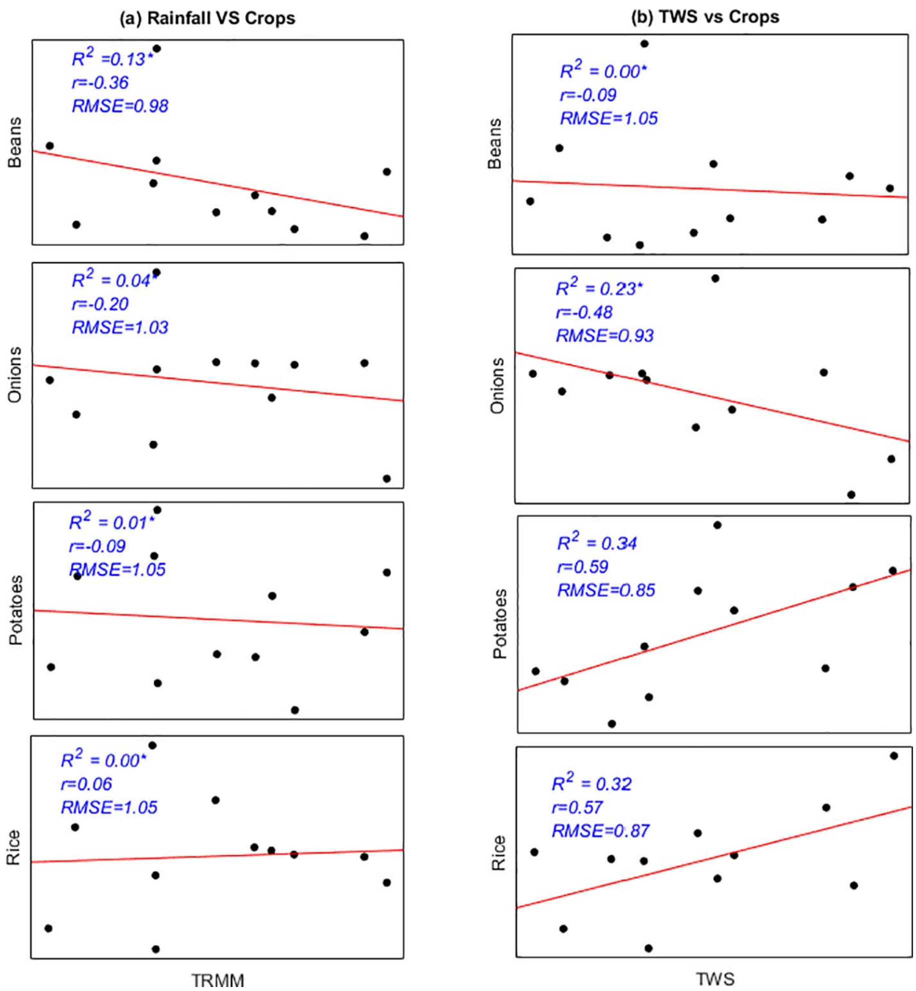

Fig. 4. Comparing the response of TWS and rainfall to crops in southern Chad. (a) Relationship between annual crop yield in Chad and average annual TRMM based precipitation anomalies over Lake Chad basin and (b) relationship between annual crop yield in Chad and TWS anomalies in the Lake Chad basin. Other regression outputs such as the slope values (*r*) and root mean square errors (RMSE) are also indicated. Asterisks (∗) show that the observed relationship is not statistically significant ($p < 0.05$).

samples of training and testing data used, generally, there are some indications that combining TWS and rainfall in a neural network can be helpful in forecasting crop yield. The various correlation values of 0.79 (potatoes vs TWS/rainfall), 0.75 (cowpea vs TWS/rainfall), and 0.80 (soybeans vs TWS/rainfall), as shown in Fig. 6b-d suggest these crops are somewhat related to the composites of TWS/rainfall. Howbeit, the response of these crops to state variables and fluxes can be significantly improved if longer times series are available for robust network training and testing. Hence, we interpret the modelling of TWS/rainfall-crop relationship with caution owing to the limited temporal series of data used in the neural network training and validation.

5. Discussion

5.1. Water availability as the driver of annual crop yield

The observed significant associations of crop yield with TWS in Figs. 3b and 4b do not negate the influence of rainfall on crop yield and vegetation dynamics in the Sahel zone as Guan et al. (2015) had reported the influence of rainfall on sorghum yields in West Africa. They argued that crop yield is fundamentally dictated by the total rainfall amount during the wet season. Consistent with previous studies (e.g., Knauer et al., 2014; Boschetti et al., 2013; Begue et al., 2011; Olsson et al., 2005; Herrmann et al., 2005) however, eccentric environmental situations exists in the Sahel, where the development of vegetation and crops are not explained by rainfall alone, instead by multiple strings of anthropogenic factors. These factors, for example, include; population displacement, change in land use pattern, improved land management, use of fertilizers, and irrigation amongst others. Since agriculture in these two riparian countries (northern Nigeria and Chad) of the basin are somewhat irrigated as rainfall is relatively low, that could explain in part the slightly higher proportion of variability explained by TWS anomalies compared to rainfall. It is known that TWS changes integrates precipitation over time and for the Lake Chad basin it is largely driven by changes in soil wetness. Given the low annual rainfall and the influence of hydraulic characteristics of the soil and increased evapotranspiration in the basin during drought periods (Ndehedehe et al., 2016b), TWS may be considered a suitable and readily available hydrological control for crops and vegetation. TWS is increasingly becoming useful in drought characterisation and monitoring of terrestrial moisture changes. Apart from its capability in the characterisation of the 2002/2003 Canadian Praire droughts, Yirdaw et al. (2008) stressed the resourcefulness of TWS as a soil moisture surrogate for drought studies in data-deficient regions around the globe, and those that show similar hydro-geological characteristics of the Canadian Prairie. Recently, TWS was also included in a suite of other multi-resolution data to characterize agricultural drought in East Africa (Agutu et al., 2017).

In spite of the foregoing results (Section 4.2), we acknowledge the fact that other human and environmental factors may introduce some uncertainties in our results, which have not been accounted for, hence the need to interpret the results with caution. For example, soil type, the use of fertilizers, root system, disease, weeds, differences in growing season, temperature, and the use of drought tolerant species (crops) amongst others may also affect the response of crop yield to TWS anomalies, rainfall and soil moisture. However, if these factors and improved farming techniques and adaptation strategies are constant, one significant factor that will determine the trajectory of agricultural yield for most rainfed agricultural systems is freshwater availability.

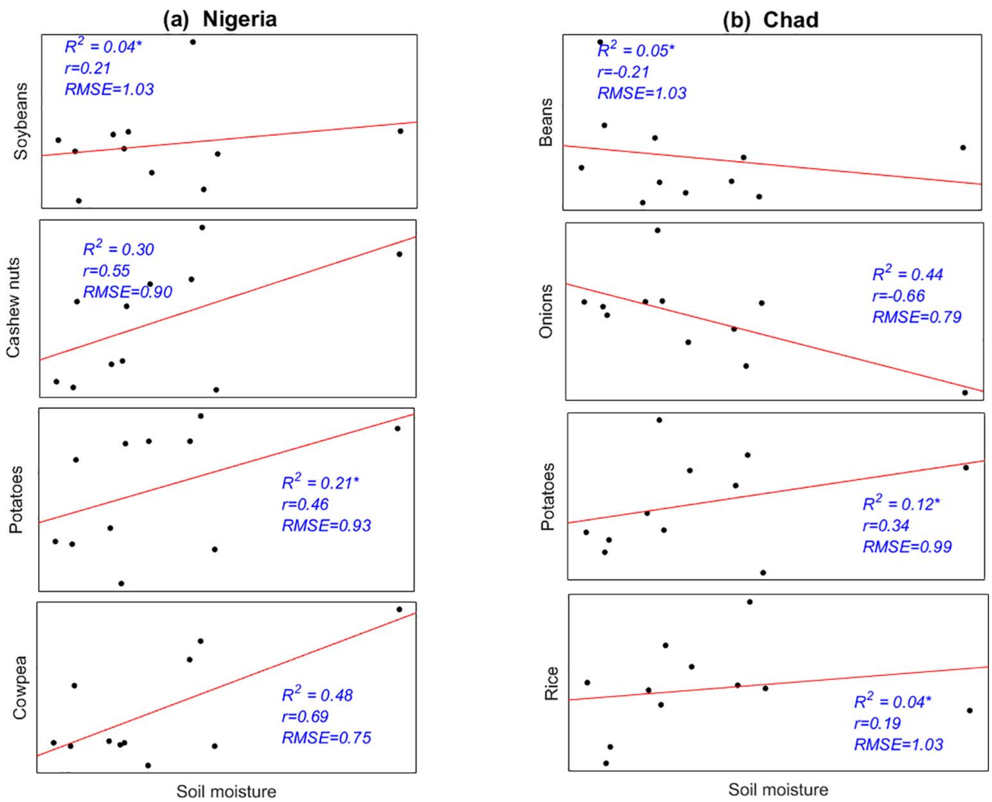

Fig. 5. Comparing the response of crops to soil moisture conditions. (a) Relationship between annual crop yield in Nigeria and average annual CPC based soil moisture anomalies over Lake Chad basin and (b) relationship between annual crop yield in Chad and average annual CPC based soil moisture anomalies over the Lake Chad basin. The crop yield data and soil moisture units have been normalised. Other regression outputs such as the slope values (r) and root mean square errors (RMSE) are also indicated. Asterisks (*) show that the observed relationship is not statistically significant ($p < 0.05$).

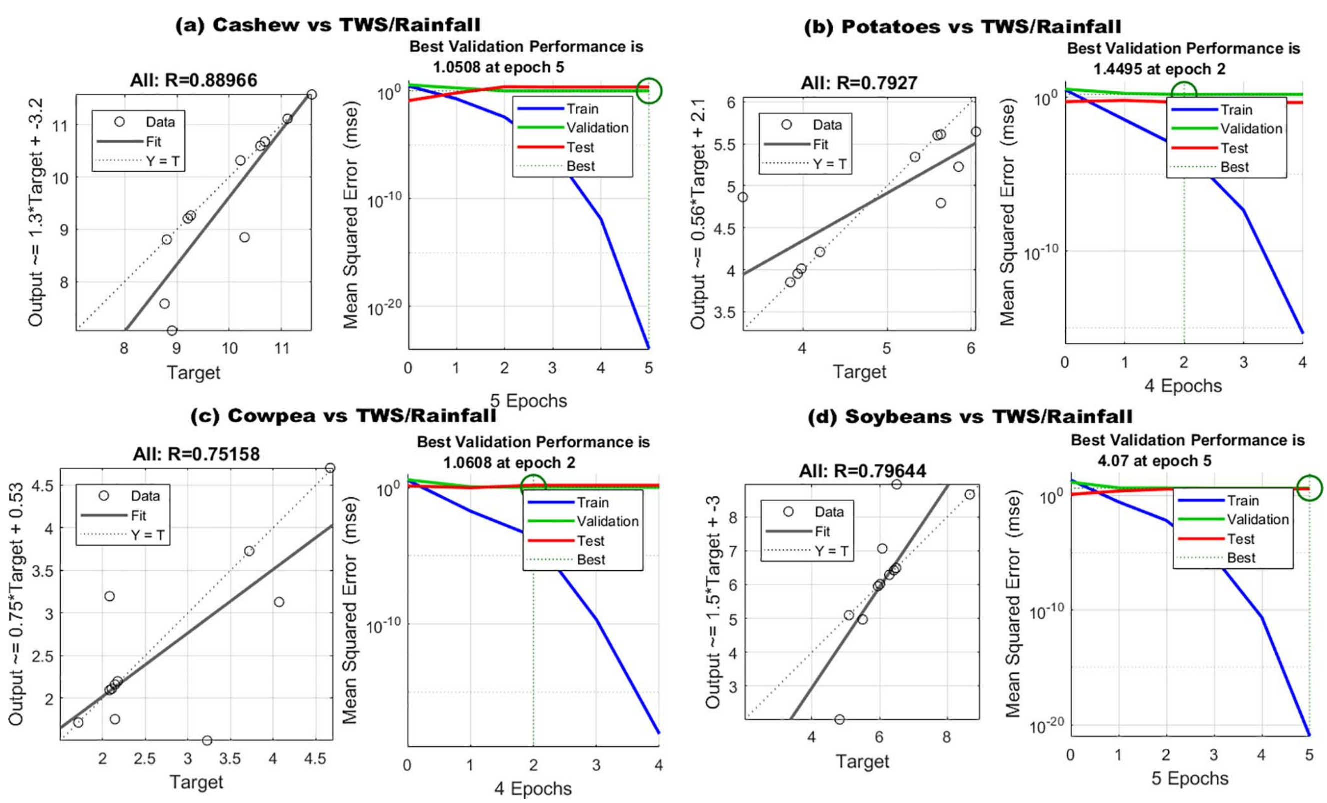

Fig. 6. Integrating TWS and rainfall in an ANN framework to assess relationship with crops. The annual crop yield and TWS/rainfall data were standardised before input into the ANN framework. The regression plots and system validation performance are indicated for (a) cashewnut vs TWS/rainfall, (b) potatoes vs TWS/rainfall, (c) cowpea vs TWS/rainfall, and (d) soybeans vs TWS/rainfall.

Since a shift in climate trends impact on water availability, crop yield arguably will be affected. Further, as indicated in Fig. 3a, rainfall explained higher proportion of the variability in soybeans (R^2 = 32%; r = 0.57%, $p < 0.05$) in Nigeria compared to TWS while the latter showed a stronger association with cowpea, cashew nuts and potatoes as opposed to rainfall (Fig. 3b). This distinction in crop response to rainfall and TWS in the region, apart from irrigation, also emanates from local (e.g., temperature), and numerous human, and environmental conditions in the sub-regions. Cashew nut, for example, shows relatively the strongest association with TWS (R^2 = 55%; r = 0.74% and apparently the lowest RMSE, $p < 0.05$) compared to other sampled crops in Nigeria (Fig. 3b). Cashew nut is a tree crop with deep tap root system that can thrive in arid environments and survives several months without water (irrigation or rainfall). As ET is a major source of water loss in the LCB (e.g., Ndehedehe et al., 2016b), increased ET could result in longer periods of soil moisture deficits. It is worthy of note that the water use mechanics of such crops could be somewhat complex owing to their ability to draw moisture from the water table region. Given the multi-layer components of TWS, which includes soil moisture and sub-surface quantities, it could be more useful in assessing the direct impacts of climate variability on the production systems of tree crops such as cashew nuts in semi-arid regions. Overall, the considerably strong association between TWS and soil moisture (Fig. 2b) supports the argument that it can serve as a soil moisture surrogate in semi-arid regions for studying water driven variability in surface vegetation and the effects of climate change on agricultural activities. The observed association between soil moisture and TWS (r = 0.95) merely suggest that changes within the multi-layer water column of GRACE-TWS are primarily within the unsaturated moisture zone. This zone responds faster to strong meteorological shifts resulting from regional climate change. The significant response of cashew nuts and cowpeas to soil moisture conditions in Fig. 4a, similar to TWS (Fig. 3b) supports this assumption. In high risk groundwater-dependent arid ecosystems where agriculture is profoundly irrigation based, increased ET owing to a rise in land surface temperature may lead to an imbalance in the water budget as rainfall is very limited and highly variable. Considering that TWS provides an overview of the water budget, in this circumstance, its potential as a suitable hydrological indicator to monitor the impact of climate variations on agricultural water use cannot be stressed enough.

It is noticed, though not absolutely general, that crops grown during the dry season (November to March) are more likely to be associated with TWS anomalies and soil moisture (e.g., cashew nuts, onions, etc.) as water supply is mostly through irrigation while those planted in the rainy season (either onset or the peak) tend to be more associated with rainfall (soybeans). Because of strong variability in annual rainfall over the region, yearly cumulations from 3 and 6-monthly rainfall did not improve the associations between rainfall and crop yields (not shown). Given that only soybeans showed a fairly significant association with rainfall (r = 0.57), it is not clear if planting season and or crop type (long cycle and short cycle) impact on observed relationship. However, in Ethiopia the narrative is different as rainfall deficits have negatively affected crop yields and have significantly contributed to food insecurity, amongst other factors (e.g., Lewis, 2017; Verdin et al., 2005 and the references therein). Furthermore, the response of crops to rainfall and TWS differ across ecological landscapes. For dry and arid Sahelian environments, where annual rainfall is relatively low and may be poorly associated with vegetation conditions due to aridity, rainfall is largely limited as a hydrological indicator for crops since agriculture is mostly irrigation based and cultivated crops are most likely drought tolerant species. Consequently, TWS could perform better than rainfall in monitoring crop yield, especially for crops grown during dry season and also those that require longer periods for optimum yield. Region-specific detailed studies in West Africa will be required to further examine such possibilities and the potential of TWS in this capacity. Nonetheless, if TWS can be considered as a low pass filter to rainfall (i.e., it's an integration of changes in rainfall over time), integrating rainfall with TWS in a predictive framework could be useful in forecasting crop yield, especially when the length of input variables are sufficiently large to support robust training and validation. Using the ANN model, such potentials have been demonstrated in Fig. 6 and confirms water availability as a key driver of crop yield in arid ecosystems. The response of crops to TWS, or to the combination of rainfall/TWS in an ANN framework as highlighted in this study nevertheless, should be interpreted with caution as longer records of GRACE-derived TWS would be required for further assessment and validation.

Further, Guan et al. (2015) believes that total rainfall during the rainy season coupled with a delayed rainy season in the arid regions of West Africa largely determines crop yield. Some local scale studies in Nigeria (e.g., Akande et al., 2012; Dugje et al., 2009), however, have argued that planting dates for soybeans and cowpea, also largely contributes to crop yield. For example, they argue that late planting may expose crops to late season pests and insufficient soil wetness condition, owing to the early cessation of rain, thereby reducing annual crop yield. Rainfall is no doubt a major catalyst and driver of hydrological conditions. But owing to aridity which is a feature of most Sahelian countries, and the other factors mentioned earlier (e.g., irrigation), it cannot by itself explain significant proportions of variability in annual crop yields. In this study, the intricacies associated with rainfall and crop yield in arid ecosystems and other environmental conditions are well noted and future studies maybe warranted in this regard in order to provide further clarification. Apart from the suitability of GRACE-derived TWS as an indicator of water availability over much of the Sahelian countries, this contribution also provides a schema for future studies, to explore extended GRACE observations as a tool to enhance our understanding of the impacts of climate variability on crop yield and agricultural production systems. Such studies will provide new perspectives on African ecology, especially in the arid ecosystems where strong positive association of TWS changes with soil moisture was found.

5.2. Implications on food security

The anticipated increase in the population of Africa would likely be met by inadequate food supply if pressing issues such as climate change adaptation, increased food production, investment in the development of water infrastructures for agricultural purposes, increased economic integration, amongst others are not included in scientific discourse. Malnutrition, hunger, and limited food supply are apparently critical indicators of food insecurity. Apart from the leading cause of food insecurity being linked to insufficient food production, sad enough, it is still a major global concern, given the estimated 1 billion people who are undergoing suffering, starvation, and malnutrition (e.g., Sasson, 2012). In an assessment of the efforts made by Economic Community of West African States (ECOWAS) towards agriculture and food security in West Africa, poverty, instability, social agitations, overpopulation, poor development of water resources, environmental degradation were identified as the hallmarks of the region (http://www.osiwa.org/ecowas_at_40/agriculture-food-security-west-africa/). The impacts of long term climatic trends in the past, which attracted the interventions of the international community and other relevant donor organizations are few indications of the long history of the region's vulnerability to extreme climatic conditions. These impacts as detailed by Benson and Clay (1994) combined with structural adjustment problems affected the economies of the region, for example, on national income through foreign-exchange availability and government expenditures.

Several challenges and constraints, e.g., lack of sophistication and modernisation of agricultural systems, combine with climatic factors to restrict agricultural development and food production system. In most sub-regions of West Africa, agriculture is heavily reliant on rainfall and largely characterised by insufficient water management, limited fertilizer use, low soil fertility, amongst other factors. Because of these, droughts and other forms of extreme changes in climate do have

devastating effects on food security and national incomes due to failure in agricultural production. For example, Haggblade et al. (2016) noted that whereas staple food production is more stable in the coastal West African region due to favourable climate, drought in the Sahelian West Africa reduces domestic rainfed cereal production by 20%. Similarly, during the 2008–2009 period in Southern Africa, more than 22 million people were classified as food insecure owing to severe drought (http://theconversation.com/sub-saharan-africa-has-a-long-way-to-go-before-it-cracks-food-insecurity-56100). Whereas drought in Sub-Sahara-SSA (includes large parts of West Africa) is the most significant climate influence on GDP (Brown et al., 2011), the need to understand the contributions of climate and the food system of the region to food insecurity has recently been emphasized (Lewis, 2017). Apart from West Africa, several other African sub-regions have experienced multiple drought events and rainfall deficits, which had considerable and significant impacts on the region's resources, contributing to famine and malnutrition (e.g., Agutu et al., 2017; Rouault and Richard, 2003; Shiferaw et al., 2014; Benson and Clay, 1994). Generally, agriculture in West Africa is sensitive to climatic conditions and for the low income Sahelian house holds, multiple climate shocks and variability are significant challenges to ensuring food security, amongst other factors. Hence, understanding the link between hydrological variability and agricultural yield supports the development of an early warning system that could mitigate food insecurity in the region.

West Africa being one of the world's poorest regions with increasing population and considerable intensity in climate extremes, under a climate change scenario, the region perhaps, could be the most vulnerable to severe water stress and human-modified drought in the nearest future. As most agricultural goods are produced in regions that are vulnerable to water-related impacts, this could have massive implications not just on food security in West Africa but other regions of the world that directly consume the agricultural goods produced in West Africa (e.g., cocoa). Water availability can therefore be thought of as a critical food security indicator that is useful for policy makers and can support risk management and monitoring efforts of relevant government agencies. The relationship of TWS with some crop yield data in northern Nigeria as observed in the regression result (Fig. 3b), for example, could be useful in a number of ways. Firstly, it can be used as a resourceful input to predict future yields in the region where there is considerable reliance on climate sensitive activities. Secondly, it demonstrates the utility of TWS as a soil moisture surrogate to assess the impacts of climate change on future scenarios of food production patterns. Given the contemporary global status on the water, energy, and food nexus (Endo et al., 2017), a renewed focus on the relationship between water availability and food security systems in the semi-arid regions of Africa and its impact on agricultural systems is critical, especially to support the formulation of policies that mitigate losses due to climate change and promote the sustainability of freshwater and food production. Further, the formulation of structural adjustment programmes and modelling of drought impacts that incorporates hydrological state variables such as TWS could enhance the region's management of available water resources to support agricultural production system. The use of satellite rainfall estimates to study the links between climate and crops in data deficient regions of West Africa are good alternatives (Ramarohetra et al., 2013). Nonetheless, as mentioned earlier in this study, they are largely restricted because of uncertainties and only provides an indirect observation of water availability (e.g., A et al., 2015; Chen et al., 2014; Yang et al., 2014). As recently showed in West Africa, satellite rainfall estimates can lead to large biases in crop modelling (Ramarohetra et al., 2013). Hence, as water availability is a major factor that limits crop growth, multi-ensemble climate modelling studies can employ TWS as a critical input to crop water balance model. This model as described in Verdin et al. (2005) evaluates moisture availability to a crop relative to its needs during the growing season. This could be useful in food production projections and improve future scenarios of crop yield production patterns.

6. Conclusions

When the prevailing climatic conditions of a typical rain-fed agricultural system changes (e.g., change to water deficits or drought conditions), plants and ecosystem services are likely to be impacted adversely in ways that could diminish agricultural productivity and increase variability in crop yields, leading to food insecurity, poverty, and other social problems. This study provides an overview of the utility of GRACE-derived TWS in assessing the impacts of climate variability on annual crop yields in a semi-arid ecosystem (the Lake Chad basin). Because of the uncertainties in water budget estimates, restrictions of rainfall as a hydrological indicator on terrestrial ecosystems, and the limited observational infrastructure for terrestrial moisture monitoring, amongst other factors, the potential of TWS to support food security assessment in a rainfed agricultural system was investigated. The use of global climate models to study the impact of climate change on West Africa's agro-ecological system is challenging owing to significant uncertainties and bias in regional climate change projections. Consequently, GRACE-derived TWS is here introduced as a new hydrological state variable to help assess the impact of climate variability on annual crop yield in a semi-arid ecosystem. The use of GRACE-derived TWS in this study to assess the impacts of climate variability on annual crop yields demonstrate the novel potential of TWS as a prominent driver of ecosystem performance that complements rainfall and soil moisture in the data deficient region. GRACE-derived TWS explained significant variability in the annual yields of some major crops in the Sahel region. This observed relationship can be used to improve crop models that will support future evaluation of the impacts of climate variability on crops.

Climate variability represents a significant challenge to water availability, which in turn influences global food production patterns. As already highlighted in this study, hydrological variability and food insecurity are prominent key features of regions in monsoonal and tropical climates. To help address some of the challenges of unmitigated impacts of climate change in these regions, especially for those tropical semi-arid ecosystems where significant proportion of annual rainfall and annual river flows are concentrated in only few months of the year, integrating TWS and rainfall in climate monitoring and forecasting will be a useful logical step in creating a dichotomy between the impacts of climate change and other socio-economic and environmental variables on national food security systems. The results from the study on the one hand, show the resourcefulness of TWS as a terrestrial moisture surrogate in studying the impacts of climate variability on the annual yield of some crops in semi-arid ecosystems. On the other hand, by integrating TWS with rainfall as input variables to model crop yield data, this study demonstrated the potential of these hydrological indicators as possible and critical inputs, amongst other parameters that could transform and benefit food security analysis.

Further, although not completely general, it is noticed that crops grown during dry season are more related to TWS as water supply is mostly through irrigation and also those that require longer periods for optimum yield. Conversely, crops planted during the rainy season tend to be more associated with rainfall. The impact of planting season and crop type (long cycle and short cycle) on the observed rainfall-crop relationship however, requires further assessment. But it is noted that other non-climatic factors could influence crop yields depending on land surface conditions, presence of weeds, and biophysical factors, amongst others. The results nonetheless, should be interpreted with caution, given the fact that longer records of GRACE-derived TWS would be required for further validation. In addition, this study sets the pace for the use of GRACE-derived TWS in monitoring the impact of climate variability on crop yield in arid ecosystems and future studies maybe warranted to provide further clarification. This study further confirms GRACE observations as a reliable tool in the data deficient semi-arid region for studies of eco-hydrological processes and advances our understanding of the impacts of climate variability on annual crop

yield. As water availability is a major factor that limits crop growth, the climate modelling community in a multi-ensemble approach can employ TWS as a resourceful tool and soil moisture surrogate to provide early warning systems and improve future scenarios of food production and crop yield projections.

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